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# Can System Dynamics learn from Social Network Analysis?

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# CAN SYSTEM DYNAMICS LEARN FROM SOCIAL NETWORK ANALYSIS?


## ABSTRACT

This article deals with the analysis of large or complex system dynamics (SD) models, exploring the benefits of a multimethodological approach to model analysis. We compare model analysis results from SD and social network analysis (SNA) by deploying SNA techniques on a pertinent example from the SD literature—the world dynamics model. Although SNA is a clearly distinct method from SD in that it focuses on social actors and their interrelationships, we contend that SD can indeed learn from SNA, particularly in terms of model structure analysis. Our argumentation follows renowned system dynamicists who acknowledge the potential of SD to synthesize and advance theories in social science at both the conceptual and technical levels.



## KEYWORDS

Social network analysis, centrality, mixing methods, model structure analysis, large models

## INTRODUCTION

This article deals with the analysis of large or complex system dynamics (SD) models, exploring the benefits of a mixing methods approach towards model analysis. For this reason, we compare model analysis results achieved by SD and social network analysis (SNA) when both methods are applied to the world dynamics model (Forrester, 1971), an example from the SD literature. We assert that, even though SNA distinguishes itself from SD by focusing on social actors and their interrelationships, SD can indeed learn from SNA. This is particularly true in terms of model structure analysis. We argue in the vein of Hovmand and Pitner (2005) and Schwaninger (2006) by acknowledging the potential of SD to synthesize and advance theories in social science.

Scholars in the systems field have shown increasing interest in mixing methods or hybrid modeling to more effectively manage complex, real-world problems. The most prominent example of this are the combinations of SD with cognitive mapping (Eden, 1994; Ackermann et al., 1997; Stotz and Größler, 2007), soft systems methodology (Lane and Oliva, 1994; 1998; Rodriguez-Ulloa and Paucar-Caceres, 2004; 2005), cybernetics (Schwaninger et al., 2004; Schwaninger and Pérez Ríos, 2008), and multicriteria analysis (Brans et al., 1998; Santos et al., 2002; Pruyt, 2007). All of these demonstrate the power and utility of a multimethodological approach. Greene et al. (2001, p.27) believe "that the fundamental uncertainty of scientific knowledge—especially about complex, multiply-determined, dynamic social phenomena—can be better addressed through the multiple perspectives of diverse methods than through the limited lens of just one."

However, mixing methods must be done carefully and with a clear purpose. Combining methods from different paradigms can cause serious problems—philosophically with respect to “paradigm incommensurability,” theoretically with respect to effectively fitting methodologies together, and practically with respect to the wide range of knowledge, skills, and flexibility required of practitioners (Burrell and Morgan, 1979; Mingers and Brocklesby, 1997). We argue that, in our case of mixing SD and SNA, theoretical coherence can be achieved with thorough argumentation. According to Lane (1999), the social theory underlying SD is not fully explicit and must be deduced from practice, revealing “functionalist sociology” as the prevailing paradigm. In contrast, SNA is a “structuralist” paradigm, conceptualizing social life in terms of the structures of relationships among actors (Carrington and Scott, 2011).

Both methods share a strong affinity towards mathematical formalization. At the heart of SNA is graph theory—a set of axioms and deductions that originated in the work of the famous Swiss mathematician and physicist Leonhard Euler (Harary and Norman, 1953). SNA is a specific application of Euler’s graph theory in which individuals and other social actors such as groups or organizations are represented in a graph by vertices or nodes and their social relations by edges or lines (Carrington and Scott, 2011). SD also has strong ties to mathematics. Forrester himself (1961) stated in his seminal and enduring book, *Industrial Dynamics*, that simulating realistic mathematical models by means of computers is one out of the four foundations of SD. Consequently, it does not come as a surprise that both SD and SNA belong to the social sciences mathematical methods.

In practice at least, the two methods have come very close. Famous system dynamicists have applied graph theory to better understand the structural complexity of large SD models and to identify structures that predominantly drive behavior (Oliva, 2004; Kampmann, 2012). This is a reasonable step because SD models can be easily described as digraphs composed of vertices and edges. These digraphs encompass entire SD models, while the vertices and edges represent variables and causal relationships respectively.

For these two reasons—their common affinity for mathematical formalization in models and the initial steps already taken towards merging two methods in practice—we believe that SD and SNA can be combined without losing theoretical consistency. The purpose of this paper is to show that a combined approach can contribute to model structure analysis, particularly to the rigor and effectiveness of SD-based model diagnosis for finding effective intervention points. Figure 1 presents the basic area of application for both SD and SNA. While SD explains the relationship between model structure and behavior, SNA is limited to characterizing model structure only.

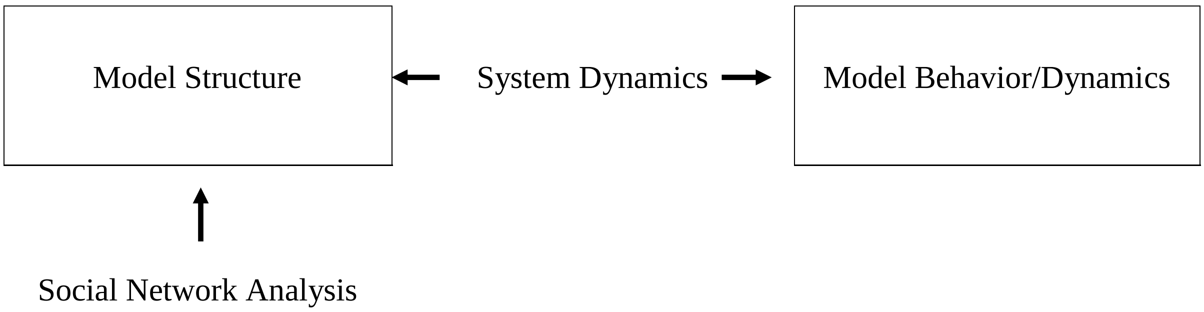


Fig. 1. Contribution of SD and SNA to model analysis

Our paper is organized into four interrelated sections following this introduction. The first section illustrates and discusses the power of SD and the type of results that can be gained with such an approach by reviewing the world dynamics model. The ensuing section presents the main concepts of SNA and demonstrates how this method can aid to model structure analysis. We show this by converting the previously introduced SD model into a graph and calculating various SNA measures and metrics. In the third section, we discuss the potential benefits of integrating SNA into SD for system dynamicists. The final section provides conclusions and recommendations for future research.

## THE POWER OF SYSTEM DYNAMICS: REVIEWING THE WORLD DYNAMICS MODEL

In 1970, the *Club of Rome* planned a project on "the predicament of mankind" with the primary objective of fostering understanding about the transition from world growth to world equilibrium. In a meeting convened that same year, discussion among club members revealed that an appropriate methodology for dealing with the broad spectrum of human affairs and the ways in which major elements of the world ecology interact could not be identified (Forrester, 1971). It was time for Forrester's system dynamics to unfold its entire methodological power and beauty by addressing this particular issue—a task that seemed insurmountable due to the inherent level of complexity generated by world dynamics.

Forrester built a 43-variable world model without counting the coefficients, interconnecting concepts from demography, economics, agriculture, and technology. He decided to use five stock variables as the cornerstones of his model: population, capital investments, natural resources, fraction of capital devoted to agriculture, and pollution. The model is capable of generating a variety of alternative behaviors depending on the policies that mankind installs to control world growth. In the following, we list the specific strengths of SD by carefully reviewing the world dynamics model.

1. SD takes the attitude of embracing complexity rather than fearing it. It has the means to effectively reduce complexity, concentrating on core elements and their interactions. While other methods are simply overwhelmed by the complexity of modeling the world system, SD is not.
2. SD generates systemic insights that lead to more fundamental problem solutions by investigating the underlying problem causes. This is in sharp contrast to other methodologies that provide only symptomatic solutions. For example, Forrester warns

that industrialization may be a more fundamental disturbing force in the world ecology than population growth, and that population explosion is perhaps best viewed as a result of technology and industrialization (Forrester, 1971).

3. SD considers problems holistically. While other methodologies had only dealt with partial aspects of the world system such as demographic change or pollution, the SD model integrates several major system-driving forces into a single model. This holistic approach is an indispensable requirement for revealing unintended and probably destructive consequences. In the case of world dynamics, these unintended consequences arise from hitting against a natural barrier or limiting condition such as the depletion of natural resources.
4. SD adopts a feedback view. All processes of growth and equilibrium occur within feedback loops: growth is generated by positive feedback loops and equilibrium by negative feedback loops. Since exploring world dynamics requires analysis of growth and equilibrium processes, it is inevitable that an appropriate method for such an analysis would take a feedback perspective.
5. SD displays results as behavior over time graphs. The methodological focus is on behavioral trends such as the identification of disruptive changes, rather than on point-precise results. Forrester (1971, p.110) recognizes that "one should not expect models of the kind discussed in this book to predict the exact form and timing of future events. Instead, the model should be used to indicate the direction in which the behavior would alter if certain changes were made in the system structure and policies." Figure 2 shows the behavior of the four stock variables—population, capital, pollution, and natural resources—simulated over a 200-year period according to Forrester's (1971) model specifications (original model). Population peaks in the year 2020 and

thereafter declines due to rapidly falling natural resources. In this mode of world behavior, the stock of natural resources is the limit to growth.

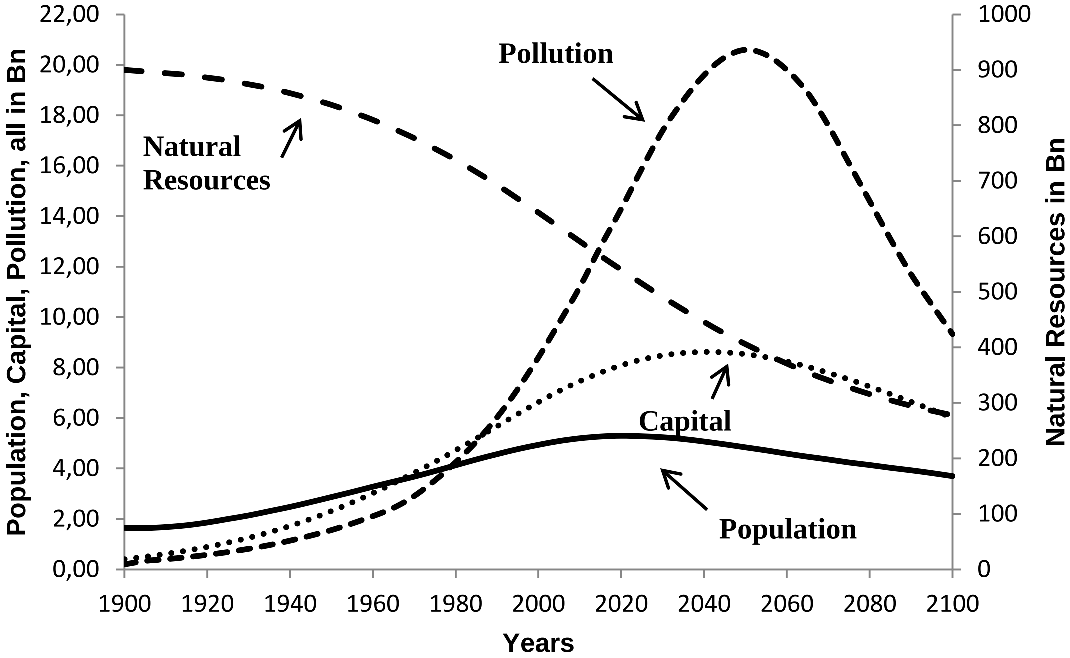


Fig. 2. Basic behavior of the world dynamics model, showing how capital accumulation and population growth are suppressed by falling natural resources

Forrester (1971) observed that the stock of natural resources is the prime limit to growth. However, if mankind succeeded in reducing the usage rate of natural resources, another more severe restraint appears—a pollution crisis. For Forrester this finding was a fundamental lesson about complex systems. When one pressure or difficulty to the system is removed, the result may be just to replace the old problem for a new, often less desirable one. Collectively, Forrester (1971) identified four limits to growth: (1) natural resource depletion, (2) pollution, (3) crowding, and (4) food shortage.

6. SD produces high-leverage and long-term solutions, respecting the objectives of the whole system. The focus is on long-term system consequences and not on short-term system improvements. Additionally, SD solutions explicitly consider the goals of the larger system, thereby avoiding the overestimation of local goals.

In chapter six of *World Dynamics*, Forrester (1971) proposes a set of changes that lead to a transition from growth to global equilibrium. He suggests the following changes: (1) reduce the usage of natural resources by 75%, (2) reduce the pollution generation rate by 50%, (3) diminish the generation of capital investments by 40%, (4) diminish food production by 20%, and (5) to lower the birth rate by 30%. These modifications mean an end to population growth and rising standards of living. Figure 3 presents this altered world scenario.

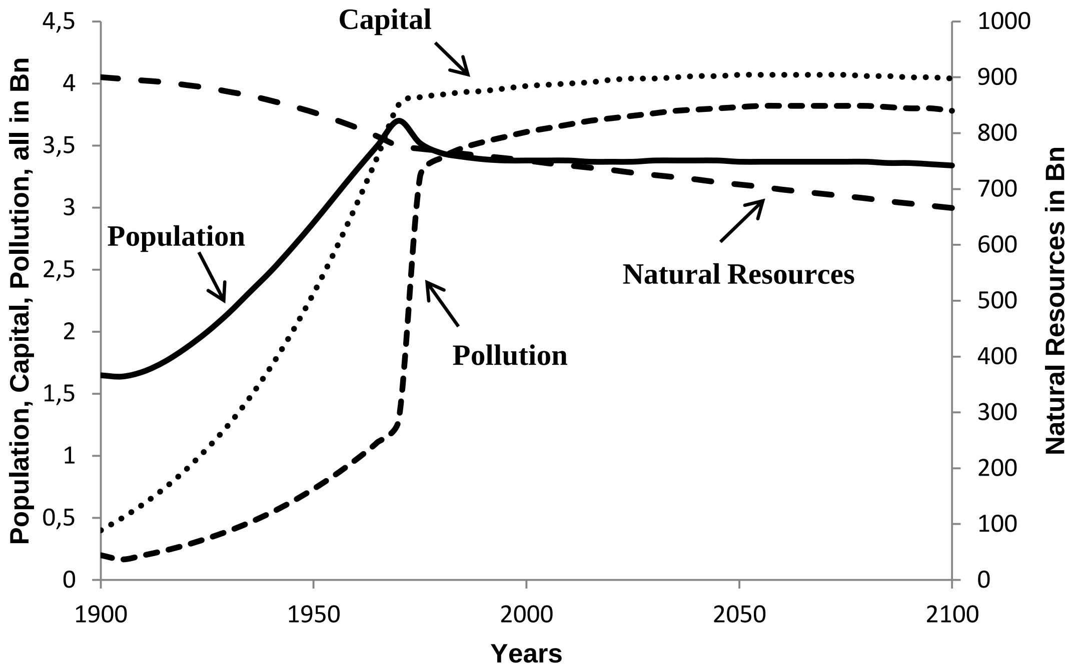


Fig. 3. Behavior of the world dynamics model after reducing pollution generation, natural-resource-usage, capital investment generation, food production, and birth rate

The world dynamics model shows that a philosophy of growth and a rising standard of living for everyone cannot be sustained. Forrester (1971, p.125) writes that “new human purposes must be defined to replace the quest for economic advancement. Nature must be helped rather than conquered. Civilization must be restrained rather than expanded. Social pressures probably must increase rather than decline, until those pressures can be transformed into a change in social values that take satisfaction from an equilibrium society.”

## SOCIAL NETWORK ANALYSIS: EXPLORING PATTERNS OF CONNECTIONS

Freeman (2004) characterizes SNA as an approach with four defining properties: (1) the intuition that links among social actors are important; (2) grounding on the collection and analysis of data that record social relations linking actors; (3) drawing substantially on graphic imagery to uncover and display the patterning of those links; and (4) developing mathematical and computational models to describe and interpret these patterns. The modern field of SNA, in the sense of Freeman’s definition, emerged in the 1930s when different researchers in the U.S. simultaneously engaged in SNA. One of these researchers, Kurt Lewin, a German psychologist, developed a structural perspective and conducted social network research *inter alia* at MIT. By the 1970s, 16 centers of social network research had appeared, however none of these centers succeeded in providing a generally accepted paradigm for the social network approach to social science research (Freeman, 2011).

In the early 1970s, this all changed due to the research of Harrison C. White and his students at Harvard University, which anchored SNA into the social sciences as a structural paradigm. In the late 1990s, physicists began publishing on social networks and triggered a revolutionary change in the field. Watts and Strogatz (1998) initiated this change when their article *collective dynamics of ‘small-world’ networks* was published in *Nature*. They discovered that many biological, technological, and social networks are seldom completely organized or random but lie somewhere between these two extremes. Watts and Strogatz (1998) call these networks "small world" networks according to the terminology used by famous American social psychologist Stanley Milgram (Milgram, 1967). Watts and Strogatz (1998), together with two other physicists, Barabási and Albert (1999), opened the door for natural scientists to explore all kinds of networks.

In recent years, two main research foci have emerged: (1) cohesive groups or communities within networks, and (2) the positions that nodes occupy in networks—a concept called centrality (Freeman, 2011). In this paper, we focus on the latter research strand by investigating the meaningfulness of applying different centrality measures on an SD model—the world dynamics model. The remainder of this section is organized as follows: first, we give a short introduction into graph theoretical descriptions of directed networks and present the four centrality measures used in SNA; second, we transform Forrester's world dynamics model into a digraph and calculate the four centrality measures for all nodes (variables) and third, we examine if the results achieved by SNA are valuable for SD modeling and analysis.

### Centrality in directed networks

A *directed network* or *directed graph*, called a *digraph* for short, is a network in which each edge has a direction, pointing *from* one vertex *to* another (Newman, 2010, p.114). One of the most convenient and compact representation of a network is the *adjacency matrix*. The adjacency matrix **A** of a directed network has the following matrix elements:

$$A_{ij} = \begin{cases} 1 \text{ if there is an edge } from\ i\ to\ j, \\ 0 \text{ otherwise.} \end{cases} \tag{1}$$

*Centrality* is one of the key topics in SNA and deals with the question, "which are the most important or central vertices in a network?" Scholars in SNA have defined differently the notion of *importance* in networks and correspondingly many centrality measures for networks exist (Newman, 2010). We will present the four most prominent measures: (1) degree centrality, (2) eigenvector centrality, (3) closeness centrality, and (4) betweenness centrality.

*Degree centrality* of a vertex in a network is simply the number of edges connected to it (Nieminen, 1974; Newman, 2010, p.133). In a directed network of *n* vertices, however, the degree of vertex *i*, $k_i$, can be further sub-divided into *in-degree* $k_i^{in}$and *out-degree* $k_i^{out}$. In-degree refers to the number of ingoing edges connected to a vertex *i*, and out-degree refers to the number of outgoing edges so connected (Newman, 2010, p.135). In- and out-degrees are defined as

$$k_i^{in} = \sum_{j=1}^{n} A_{ji}, \qquad k_i^{out} = \sum_{j=1}^{n} A_{ij}. \tag{2}$$

*Eigenvector centrality* is a more sophisticated version of the degree centrality explained previously in this paper. Eigenvector centrality takes into account that not all neighboring vertices of a vertex *i* are equivalent. One can argue that, in many circumstances, it is reasonable to assume that the importance of a vertex in a network is increased by having connections to other vertices that are themselves important (Bonacich, 1972; 1987; Newman, 2010). Mathematically, eigenvector centrality is defined as

$$x_i = \kappa_1^{-1} \sum_{j} A_{ij}\, x_j, \tag{3}$$

where $\kappa_1$is the largest eigenvalue of adjacency matrix **A**.

Thus, the reason for a vertex *i* to have large eigenvector centrality is either because this vertex has many neighbors or because it has important neighbors (or both). For example, an individual in a social network can be important, according to eigenvector centrality, both because he or she knows a lot of people or because he or she knows a few, people who are very influential (Newman, 2010).

*Closeness centrality* measures the mean distance from a vertex to all other vertices. Suppose $d_i$ is the length of a *shortest path* from vertex *i* to *j*, then the average shortest path from *i* to *j* over all vertices *j* in the network is (Sabidussi, 1966; Newman, 2010, p.181)

$$l_i = \frac{1}{n} \sum_j d_{ij}. \tag{4}$$

The average shortest path, $l_i$, is not a centrality measure in the same sense as degree centrality: it gives low values for more central vertices and high values for less central ones. For this reason, SNA researchers commonly calculate the inverse of $l_i$ rather than $l_i$ itself. This inverse is called the closeness centrality, $C_i$, and is defined as

$$C_i = \frac{1}{l_i} = \frac{n}{\sum_j d_{ij}}. \tag{5}$$

*Betweenness centrality* measures the extent to which a vertex *i* lies on paths between other vertices (Freeman, 1977; Newman, 2010, p.185). This centrality measure is based on the network flow model (Borgatti and Lopez-Kidwell, 2011), where information or a resource flows from vertex to vertex along paths. Freeman (1977) made the simple assumption that every pair of vertices connected by a path in the network exchanges information with equal probability per unit time and that information always takes the shortest path—or randomly chooses one of equal shortest paths—through the network. This assumption implies that if we wait a suitably long time until a lot of information is exchanged between vertex pairs, the amount of information passing through each vertex is simply proportional to the number of shortest paths on which the vertex lies. This number of shortest paths is the betweenness centrality (Newman, 2010). In mathematical terms, let $n_{st}^i$ be 1 if vertex *i* lies on a shortest path between vertex $s$ and $t$ and 0 if it does not or if there is no such path, then the betweenness centrality $x_i$ is defined as

$$x_i = \sum_{st} n_{st}^i. \tag{6}$$

Equation (6) can be normalized on a logical scalar with *n* as the number of vertices as follows

$$x_{i,NORM} = \frac{2 * x_i}{(n * n - 3 * n + 2)}. \tag{7}$$

**The world dynamics model as a directed graph**

We have slightly simplified Forrester's world dynamics model by eliminating the lookup variables (time tabs) from the model. The resulting model contains 59 vertices and 88 edges (see appendix for the list of variables used). We compiled the adjacency matrix with the corresponding data and used *Gephi,* an open-source graph visualization and manipulation software, to display the directed network (see Figure 4). Next we calculated all four centrality measures introduced in the previous section for each vertex and sorted the results in descending order. In the following, we present only those 10 vertices for each centrality measure that have achieved the highest centrality score. For this analysis task we used *R*, a free software environment for statistical computing and graphics together with the free software package *igraph* (see appendix for the *R* code). Table 1 shows the 10 most important vertices according to the degree centrality. For vertices having the same degree, those with a higher out-degree are assumed to be more important. The vertex numbering in Table 10 corresponds to the vertex numbers in the adjacency matrix in the appendix.

Table 1. 10 most influential vertices with respect to the degree centrality (S = stock, F = flow, A = auxiliary variable; italicized vertices represent intervention points proposed by Forrester to reach world equilibrium)

| Vertex | Name | Degree | Out-degree | In-degree |
|---|---|---|---|---|
| **1** | Population (S) | 9 | 7 | 2 |
| **17** | *food ratio* (A) | 9 | 4 | 5 |
| **28** | material standard of living (A) | 7 | 5 | 2 |
| **57** | pollution ratio (A) | 7 | 5 | 2 |
| **8** | crowding (A) | 7 | 4 | 3 |
| **36** | Capital Agriculture Fraction (S) | 7 | 3 | 4 |
| **15** | *births* (F) | 7 | 1 | 6 |
| **2** | deaths (F) | 7 | 1 | 6 |
| **31** | capital ratio (A) | 5 | 3 | 2 |
| **30** | effective capital ratio (A) | 5 | 1 | 4 |

Owing to the purpose of this model—transition from world growth to world equilibrium—it is not surprising that population is the most influential vertex according to the degree centrality and all other centrality concepts (shown in Table 2). Although food ratio has the same degree as population, it probably has less influence on the world dynamics model due to the smaller out-degree. The 10 most influential vertices related to degree centrality include only two of the intervention variables suggested by Forrester to stabilize population growth—food ratio and births—meaning that the other three intervention variables do not exhibit adequately high degree. Table 10 shows that both material standard of living and pollution ratio have significant impacts on the model, and might also serve as effective leverage points to influence world growth.

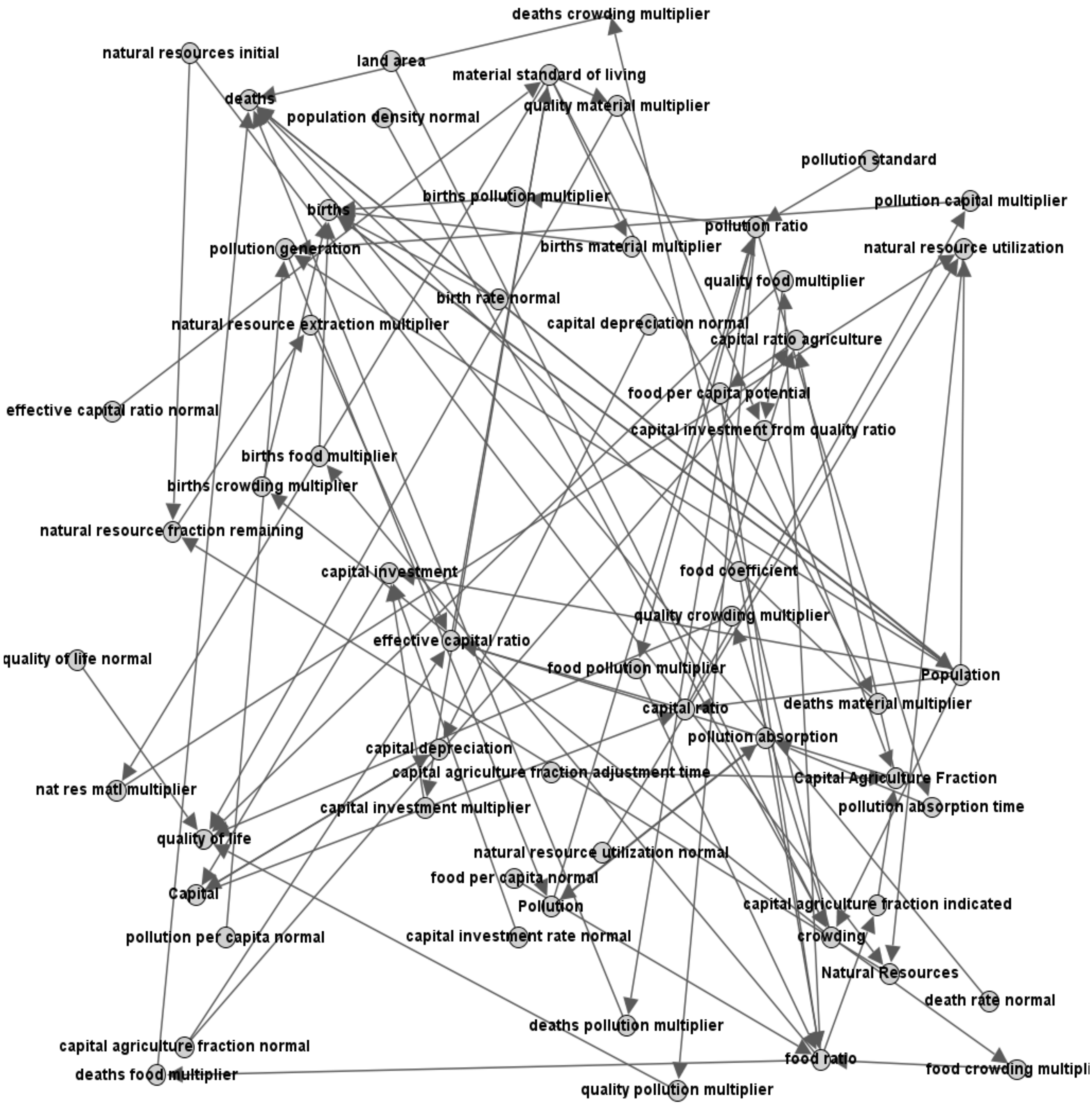


Fig. 4. The world dynamics model converted into a directed network

Table 2 presents the 10 most important vertices with respect to eigenvector, closeness, and betweenness centrality. In contrast to simple degree centrality, eigenvector centrality reveals in the first 10 vertices four out of five of the intervention points chosen by Forrester: births, capital investment, pollution generation, and natural resource utilization.

Table 2. 10 most influential vertices with respect to the eigenvector, closeness, and betweenness centrality (S = stock, F = flow, A = auxiliary variable; italicized vertices represent intervention points proposed by Forrester to reach world equilibrium)

| **Eigenvector** | | | **Closeness** | | | **Betweenness** | | |
|---|---|---|---|---|---|---|---|---|
| **Vertex** | **Name** | **Centrality** | **Vertex** | **Name** | **Centrality** | **Vertex** | **Name** | **Centrality** |
| **1** | Population (S) | 1 | **1** | Population (S) | 0.3892617 | **1** | Population (S) | 0.7307925 |
| **15** | *births* (F) | 0.675780 | **15** | *births* (F) | 0.3452381 | **28** | material standard of living (A) | 0.5290381 |
| **2** | deaths (F) | 0.675780 | **2** | deaths (F) | 0.3452381 | **30** | effective capital ratio (A) | 0.5102843 |
| **8** | crowding (A) | 0.444859 | **31** | capital ratio (A) | 0.3452381 | **15** | *births* (F) | 0.3563218 |
| **31** | capital ratio (A) | 0.388921 | **8** | crowding (A) | 0.3372093 | **2** | deaths (F) | 0.3563218 |
| **25** | *capital investment* (F) | 0.313388 | **17** | *food ratio* (A) | 0.3222222 | **45** | Pollution (S) | 0.3200242 |
| **46** | *pollution generation* (F) | 0.308412 | **28** | material standard of living (A) | 0.3186813 | **17** | *food ratio* (A) | 0.3106473 |
| **54** | *natural resource utilization* (F) | 0.282348 | **30** | effective capital ratio (A) | 0.3186813 | **57** | pollution ratio (A) | 0.3079250 |
| **11** | births crowding multiplier (A) | 0.252337 | **46** | *pollution generation* (F) | 0.3085106 | **31** | capital ratio (A) | 0.284634 |
| **7** | deaths crowding multiplier (A) | 0.252337 | **54** | *natural resource utilization* (F) | 0.3085106 | **46** | *pollution generation* (F) | 0.2758621 |

It makes sense that eigenvector centrality attaches more importance to Forrester's leverage points, because four of them are flows that are by definition connected to highly influential neighbors—the stocks. As eigenvector centrality values vertices with important neighbors more highly than those with less influential neighbors, vertices representing flows in the world dynamics model receive a higher score than with simple degree centrality. The eigenvector centrality concept recognizes that both births and deaths occupy very central positions in the network and are effective levers for controlling world growth. This finding is not surprising to system dynamicists at all, since it is common sense among SD practitioners that every stock is controlled by its inflow (births) *and* its outflow (deaths). In addition to Forrester's leverage points, eigenvector centrality suggests that crowding and capital ratio also exert a substantial influence on the model and may be suited for intervention.

As mentioned in the preceding section, the closeness centrality of a vertex is the inverse of the average shortest path of this vertex to all other vertices in the network. Thus, a central vertex is one that, if changed, transmits those changes very quickly to the entire network. The 10 most central vertices in the network with respect to closeness centrality again include four of the leverage points proposed by Forrester. This time they are births, food ratio, pollution generation, and natural resource utilization. The first five vertices calculated with closeness centrality are exactly the same as the ones calculated with eigenvector centrality, except that capital ratio and crowding have switched places. Furthermore, the closeness centrality concept considers material standard of living and effective capital ratio to be important vertices in the network.

Betweenness centrality is a very different measure of centrality than the others presented before. It specifies the extent to which a vertex lies on paths between other vertices. Vertices with a high betweenness centrality may have extensive influence within a network by virtue of their control of information flowing *between* others. The removal of these vertices more than any others will disrupt communication between other vertices because they lie on the largest number of paths taken by information flows (Newman, 2010). Among the 10 most important vertices according to betweenness centrality, three intervention variables indicated by Forrester appear: births, food ratio, and pollution generation. In contrast to eigenvector and closeness centralities, betweenness centrality attributes a higher influence to material standard of living and effective capital ratio.

The results of these four different centrality analyses are very promising. They confirmed many of Forrester's intervention variables as being also central vertices in a directed network, and pointed to variables such as capital ratio or crowding that are suited for intervention but were not in the spotlight in Forrester's book (1971).

## INTEGRATION OF SNA INTO THE SD MODELING AND ANALYSIS PROCESS

We believe that the centrality measures from SNA are a good complement to the formal model analysis techniques of SD. Centrality analyses can serve as a first screening of large SD models to identify potential levers in the model. SNA techniques might be integrated into the SD process after system mapping and before the formulation of a simulation model. Such an additional structural analysis can be very helpful for system dynamicists for the design of alternative policies and structures (step 5). Traditionally, these alternatives come from intuitive insights generated in preceding steps of the SD process, from the experience of the modeler, from people operating in the system of interest, or by an exhaustive automatic testing of parameter changes (Forrester, 1994). Thus, the design of effective alternative policies is difficult—particularly for novice modelers—and a strategy for preliminary centrality analyses will be much appreciated. Figure 5 shows the SD modeling and analysis process extended by a model structure analysis step (step 2). The SD process is highly iterative, with many feedbacks on preceding steps. For reasons of clarity, we neglected to show these feedbacks in Figure 5.

| Step 1 | Step 2 | Step 3 | Step 4 | Step 5 | Step 6 | Step 7 |
|---|---|---|---|---|---|---|
| describe the system (system mapping) | model structure analysis (e.g., centrality analyses) | model formulation | model simulation | design alternative policies and structures | educate and debate | implement changes in polices and structures |

Fig. 5. Extended SD process based on Forrester (1994)

## CONCLUSIONS

This article argues that the integration of SNA techniques into the SD modeling and analysis processes can be very valuable, in particular for inexperienced modelers. As system modeling is a highly demanding task, novice system dynamicists can be easily overwhelmed and lose perspective in an SD project. Every modeler, experienced or not, is confronted with two basic problems: *how* to best describe or model the system, and *where* to change the system to produce more favorable system outcomes. We argue that centrality analyses can help modelers address the latter problem by providing a screening tool for finding effective levers in large SD models. We think that such an additional structural analysis integrated early in the SD process increases the effectiveness of designing alternative polices and structures.

By representing an SD model as a directed network, we limit ourselves to its structural complexity and neglect the dynamic complexity that emerges from its nonlinear relations and accumulations. It is clear that SD is most interested in system behavior and not in structure *per se*. However, one of the core presumptions of SD emphasizes that system behavior arises from underlying system structure (Meadows, 1989; Oliva, 2004). Often, changing the system structure is the only way to alter undesired or pathological system behavior. Having better tools available to understand and simplify structural complexity permits a more efficient policy design process (Oliva, 2004).

This article discusses the value of centrality analyses in the SD process by means of one prominent case. Future research should be directed towards a more systematic investigation of the benefits of such model structure analyses by evaluating multiple SD models.

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# APPENDIX

Table A. Variable list

| Number | Variable name | Number | Variable name |
|---|---|---|---|
| 1 | Population | 31 | capital ratio |
| 2 | deaths | 32 | capital ratio agriculture |
| 3 | death rate normal | 33 | capital agriculture fraction normal |
| 4 | deaths pollution multiplier | 34 | quality material multiplier |
| 5 | deaths material multiplier | 35 | capital investment from quality ratio |
| 6 | deaths food multiplier | 36 | Capital Agriculture Fraction |
| 7 | deaths crowding multiplier | 37 | capital agriculture fraction adjustment time |
| 8 | crowding | 38 | quality of life |
| 9 | population density normal | 39 | quality crowding multiplier |
| 10 | land area | 40 | quality food multiplier |
| 11 | births crowding multiplier | 41 | quality pollution multiplier |
| 12 | births food multiplier | 42 | quality of life normal |
| 13 | births pollution multiplier | 43 | capital depreciation normal |
| 14 | births material multiplier | 44 | capital depreciation |
| 15 | births | 45 | Pollution |
| 16 | birth rate normal | 46 | pollution generation |
| 17 | food ratio | 47 | pollution per capita normal |
| 18 | food pollution multiplier | 48 | pollution capital multiplier |
| 19 | food coefficient | 49 | natural resource fraction remaining |
| 20 | food per capita normal | 50 | natural resource extraction multiplier |
| 21 | food per capita potential | 51 | natural resources initial |
| 22 | capital agriculture fraction indicated | 52 | Natural Resources |
| 23 | food crowding multiplier | 53 | nat res matl multiplier |
| 24 | Capital | 54 | natural resource utilization |
| 25 | capital investment | 55 | natural resource utilization normal |
| 26 | capital investment rate normal | 56 | pollution standard |
| 27 | capital investment multiplier | 57 | pollution ratio |
| 28 | material standard of living | 58 | pollution absorption time |
| 29 | effective capital ratio normal | 59 | pollution absorption |
| 30 | effective capital ratio | | |

Table B. R code

```
# load package in R
library ("igraph")
# data import
setwd("C:/Users/Name/Documents/Universität/Network Analysis")
edgelist <- read.table('World Model.txt', header=T)
WorldModel <- graph.data.frame(edgelist, vertices=data.frame(id=1:max(edgelist[,1:2])))
summary (WorldModel)
## local characteristics:
# degree centrality (In & Out = all, In = in, Out= out)
degree <- degree(WorldModel, mode="in")
degree
write.csv(degree, file = "degree.csv")
# Eigenvector Centrality
EVcent <- evcent(WorldModel, scale=T)$vector
EVcent
write.csv(EVcent, file = "EVcent.csv")
# Closeness Centrality
Clocent <- closeness(WorldModel, mode = c("all"), normalized=T)
Clocent
write.csv(Clocent, file = "Clocent.csv")
# Betweenness Centrality
Betcent <- betweenness(WorldModel, directed = TRUE, normalized=F)
Betcent
write.csv(Betcent, file = "Betcent.csv")
```